Seastate detection from vessels at motion using learning algorithms

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Abstract

The seastate a vessel encounters directly impacts its operation by impacting fuel efficiency or causing motion sickness. Many vessels don't have access to seastate information due to a lack of commercial viability for available sensing systems. Austal is conducting large scale data collection trials to better understand seastate conditions around their vessels and vessel condition monitoring to improve client operations. This project uses a dataset provided by Austal to develop a method for estimating seastate around a vessel with forward speed using the available dataset.

To accomplish this, vessel motion measurements from the dataset of an in-service vessel were utilised to develop new models to estimate the significant wave height, peak wave period and mean wave direction. As the vessel motions are filtered due to the vessel complexity this project focused on estimating seastate conditions that influence vessel motions. To develop the model a machine learning algorithm has been employed to solve the system complexities.

Using this process, a vessel with forward speed can estimate seastate conditions. Additional scope was used to determine the most important features, at what rate the model can predict seastate parameters and the quantity of data required to train a model to a similar accuracy.

1. Introduction

Fuel consumption is the largest incurred expense for a vessel, many operators focus on improving fuel efficiency. Most methods for improving fuel consumption have been single settings options that are implemented at the start of a voyage or seasonal based. Austal wants to develop a fuel consumption model that can predict fuel consumption across multiple conditions to dynamically set the optimal vessel settings. Seastate has been determined to be a key parameter in this model that needs to be accurately obtained in real time.

Seastate conditions are typically characterised using three statistical parameters (DNV, 2007):

- Significant wave height (H_s): The average height (trough to crest) of the highest one-third of waves in an indicated time period, also commonly denoted $H_{1/3}$
- Peak wave period (T_P): The wave period ω responding to the maximum of the wave energy spectrum
- Mean wave direction (β): The mean direction from which the waves approach a location, with respect to North or heading

Wave buoys are a common method for obtaining wave statistics/spectra and are widely used for their accuracy. They record motion using an Inertia Measurement Unit (IMU), that measures the acceleration and rate of rotation for wave-induced motions. Post processing is performed using spectral analysis, which decomposes motion measurements into the wave spectra to determine statistical wave properties. Wave buoys are able to calculate these properties as they were designed to be an easily interpreted system that responds to seastate, however, this technique is unsuited to the complex designs of in-service vessels.

In many locations around the world, wave buoy data is not available, numerical hindcast models are unreliable or not practical, and physics-based models can produce multiple results for similar seastate conditions. There are different techniques to collect this data from a vessel which can be used to determine seastate. These include surface displacement, motion readings and visual recordings. The seastate measurements collected are then estimated using methods such as zero crossing analysis (Wall, 2003), wave spectral analysis (Tannuri et al., 2003) and other seastate algorithms. However, many of these on-vessel methods of estimating seastate are not applicable for vessels with forward speed as it adds significant complexity.

The waves that are detectable from measuring vessel motions are those that induce vessel motion. These waves are wind driven waves as shown in Figure 1. This is acceptable as this study is only interested in seastates that affect the vessel.

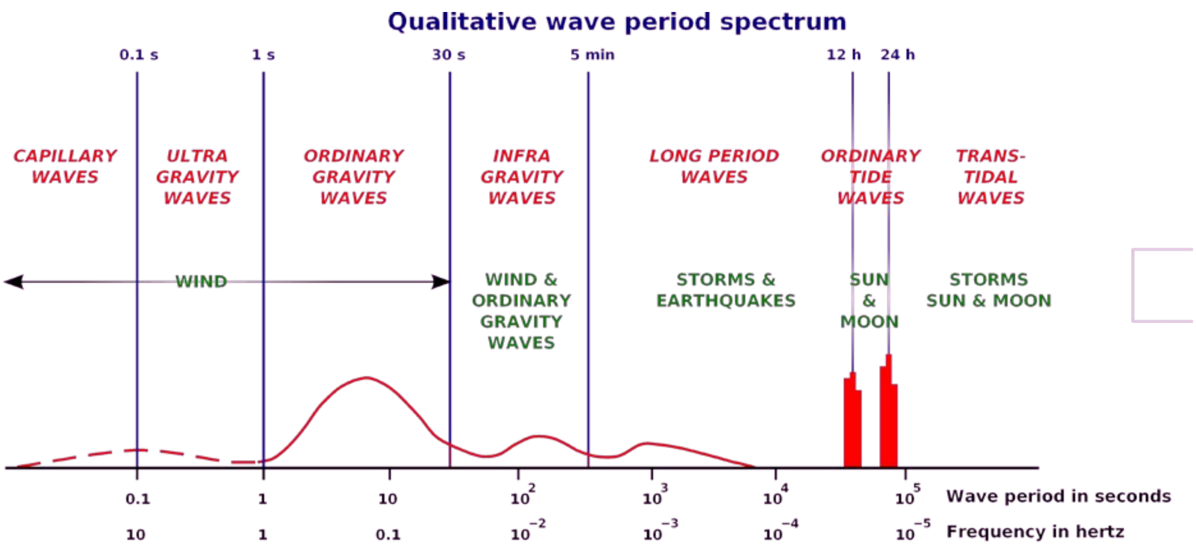

Figure 1 Wave power spectrum (Munk, 1950)

Machine learning has become a popular tool for solving complex, pattern-based applications. Machine learning is the application of computer algorithms capable of learning to predict results based on their own previous experiences. The algorithm functions by inputting a set of "features" known as an "observation" that can be understood by the computer (Pedregosa et al., 2012). These features are then transformed into singular or multiple outputs or "labels" as seen in Figure 2.

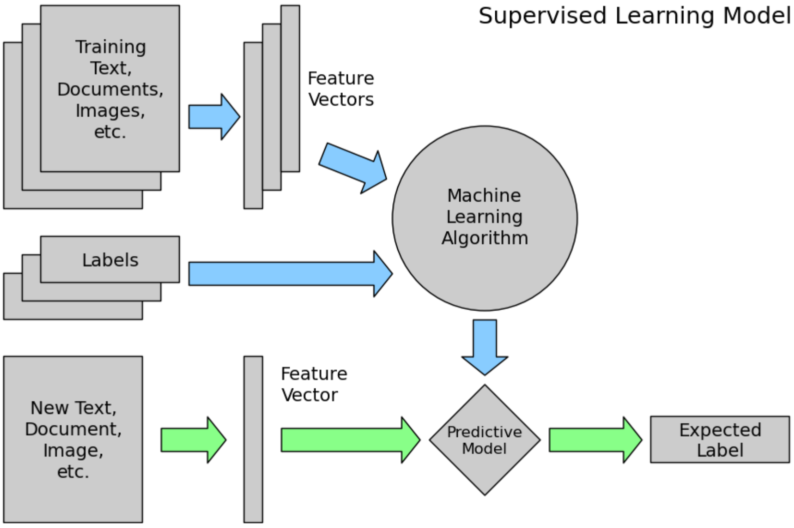

Figure 2 ***Example of supervised machine learning model***

The available dataset will be used to evaluate the potential of estimating the total seastate parameters by applying a machine learning strategy. The estimated seastate will be limited to seastate conditions that excite the vessel and modelling will be limited to a single vessel for a single site.

2. Process

Machine learning will be used to identify the unique sea state conditions and their impact on the vessel. To evalute sea state conditions around a vessel, the vessel motions have been recorded, enabling machine learning models to learn by providing a validation source. For the project a wave buoy will be used for its accuracy in the environment of the trial.

The wave buoy chosen to train the model is the Cottesloe wave buoy (Australian Ocean Data Network, 2018) and is a Waverider MkIII. This will act as an independent measure of wave data for its location and accuracy. The wave buoy measures with an uncertainty for significant wave height of ± 0.01 m, Peak wave period ± 0.5 s and mean wave direction ± 2 ° (Datawell, 2012).

2.1 Measurement/ Field campaign

The dataset used for this study was acquired on the Rottnest Express ferry “Eagle Express”. The vessel data was acquired during its normal operation as it travelled between Rottnest Island and Fremantle. The vessel motions were recorded with an onboard 6-axis IMU at 20 Hz attached to the vessel’s hull and a GPS at 1 Hz located in the bridge.

Typical wave conditions for the trial area represent typical data collected to be used for model training. Data collected from 2018 supplied from the DoT (Department of Transport, 2018). Typical significant wave height can range from 0.5 to 1.5 m. Typical peak period ranges from 10 to 16 s. Typical sea and swell direction can range from 225 to 270 degrees with respect to north.

The vessel has a monohull and is 34.75 m in length, has a beam of 7 m and a displacement of 80.45 tonne. It travels at about 13 m/s over a distance of 20 km based on the data from the middle section as shown in Figure 3. 33 hours of vessel movements were recorded for the trial over many voyages across varying seastates.

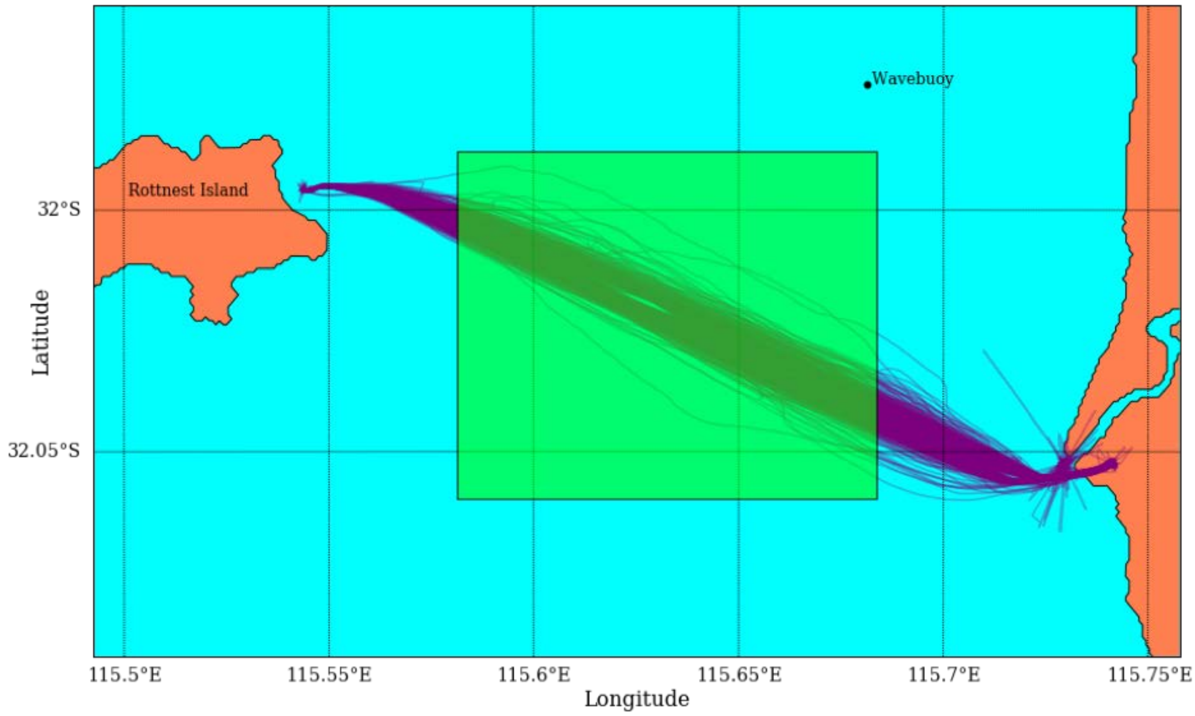

Figure 3 Map with recorded data showing a shaded area where data will be used for model training

2.2 Modelling strategy

Grey-box modelling is used as the modelling strategy, which uses a white box approach (knowledge of the system) that is then applied to a Black-box model (Machine learning). This allows the model to incorporate the physics of the model together with the advantages of black-box improved performance. It has been modelled in series where the white-box theory then calculates better features that will train the black-box model as shown in Figure 4.

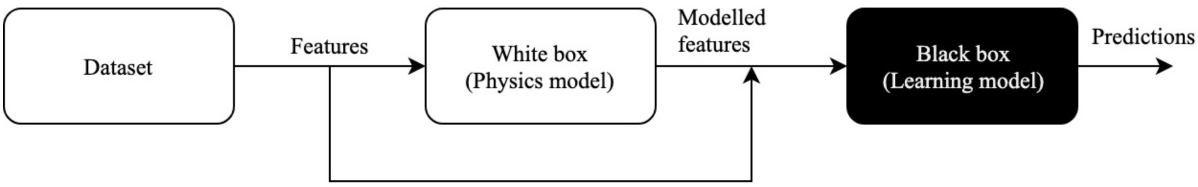

Figure 4 Graphical approach to modeling

To best evaluate which black-box model performs better, multiple models have been selected for testing. The modelling methods that have been evaluated are decision tree regression, Support Vector Machine and neural network. All models were modelled using the python programming language and the libraries scikit learn and tensorflow.

The features were modelled using a series of measurements and taking the statistical properties for a set of readings. The literature shows the most influential features may be the standard deviation of acceleration and the rate of rotation around the primary axis. The covariance between two axes of motion was identified as an important feature for determining wave direction.

Models require a method of evaluating how successfully they predict the labels to compare against different models. In order to evaluate the accuracy of a model, the root mean square error (RMSE) has been used as the performance metric. This is a common modelling quality metric, where a lower RMSE is the desired outcome.

3. Results and Discussion

Creating unique models for each predicting element by varying features, modelling method and learning method allows the models to be studyed to deteremine the positives and negatives for each strategy. This permits more accurate and sophisticated models to be developed to determine sea state conditions.

3.1 Modelling method comparison

To determine the best modelling method each condition was trained for a series of recordings then the RMSE was averaged for each method. The best model is determined by varying features, time interval for each observation and modelling strategy. This is repeated for each predicting sea state variable. The results show that different sets of inputs are optimal for different parameters.

3.2 Quantity of data required

To determine the quantity of data required for modelling each parameter, the training dataset was reduced and evaluated. Scores are based on a normalised RMSE from the best model of each parameter. A key interpretation is how much data is required to train a model for 90% accuracy for its best model, as seen in Figure 5.

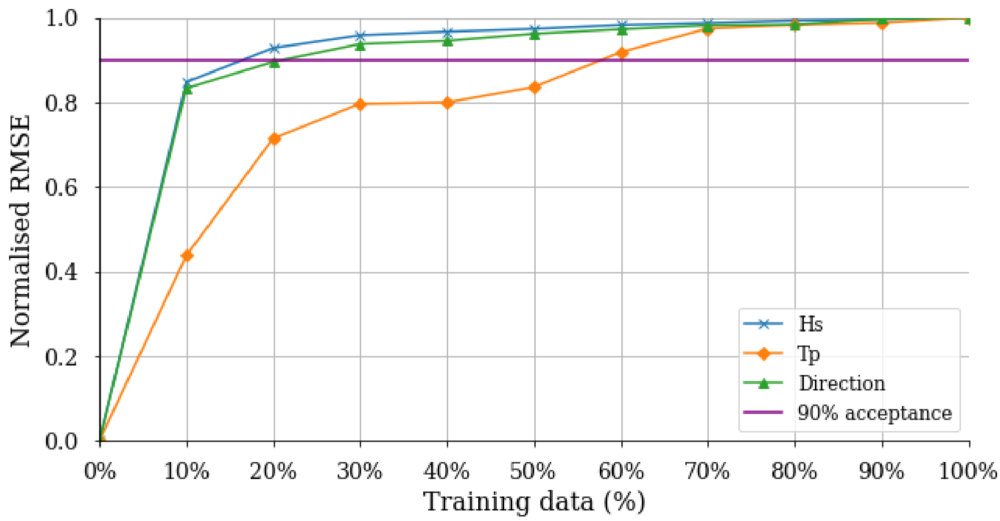

Figure 5 Graph demonstrating training dataset for modelling vs performance

4. Conclusions and Future Work

This trial was conducted on an in-service 35 m monohull vessel consistently operating between two locations. This trial has shown that with knowledge of vessel motions, speed and heading, seastate can be estimated.

This method is useful for locations where only a segment of the journey can be used for training. For example, the area around a wave buoy or other point of truth. This model can be used to estimate seastate data for the whole journey to assist on-vessel operations. This method shouldn't have any key obstacles for training in different locations unless there are severe differences in seastate that can't be trained in the location.

As this trial was conducted on a 35 m vessel with no ride control systems, the vessel was directly impacted by seastate conditions. For larger vessels with ride control systems, it is not immediately apparent how accurately this system will scale up. An additional trial applying this procedure to a larger vessel would help validate the method.

In most scenarios, vessels want to be able to immediately apply these methods without a lengthy data collection stage. A method to improve this is to "Fast start" a model by training an initial model on simulated data and then incorporating real data as it becomes available. This method could greatly improve the amount of data required to train a model to an acceptable level.

5. Acknowledgements

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